# Making gait recognition robust to speed changes using mutual subspace method

Yumi Iwashita[1], Mafune Kakeshita[2], Hitoshi Sakano[3] and Ryo Kurazume[2]

***Abstract*— Mutual subspace method (MSM), which is one of image-based approaches, showed strong discrimination capability in gait recognition. In general, 2D image matrices are transformed into 1D image vectors to be used as input into MSM, and then principal component analysis (PCA) is applied to 1D vectors to generate a subspace. However, due to the high dimensionalities of 1D vectors, the evaluation accuracy of the covariance matrix in PCA is not high enough. This results in a decrease in performance, especially in case that speed difference between gallery and probe dataset is big. Thus in this paper we propose a method, which expands the MSM-based method, to recognize people with higher accuracy. The proposed method divides the human body area into multiple areas, followed by adaptive choice of areas that have high discrimination capability. Moreover, the proposed method utilizes the frieze pattern, which is one of gait features, as an additional input into MSM. The use of divided areas and the frieze pattern allows us to evaluate the covariance matrix with higher accuracy. In experiments we applied the proposed method to challenging databases with speed variations, and we show the effectiveness of the proposed method.**

## I. Introduction

Gait is one of biometrics which do not require any interaction with a subject and can be obtained from a distance. Gait-based person recognition has been providing new opportunities in various applications, such as surveillance system in public [6] and personalized robots which provide adaptive service to people [11]. In general, gait-based person identification methods extract features from time-series gait images, followed by person identification based on extracted features. There are many existing methods for feature extraction, such as gait energy image (GEI) [5], active energy image (AEI) [20] and frame difference frieze pattern (FDFP) [16], which reported good performance with publicly available gait databases [8] [1].

However, there are several causes which make the performance of gait recognition worse. Since appearance-based method is sensitive to appearance changes, the performance can be worse in case that a subject's appearance is different from that in the database. A possible situation is walking speed change. The walking speed change causes variations in pitch and stride, which result in appearance changes. To address this problem, existing methods have focused on transforming the gait features from various speeds into a common walking speed or on extraction of speed-invariant gait feature. Mansur et al. proposed a method [15] which utilized a cylindrical manifold to synthesize constant-speed gait images. Zeng et al. proposed a method for gait recognition based on silhouette features with deterministic learning theory (DLT) [19]. Guan et al. proposed a classifier ensemble method based on Random Subspace Method (RSM) concept [4]. Experimental results with OU-ISIR Treadmill Dataset A [13] by the RSM-based method showed the best performance compared with other methods.

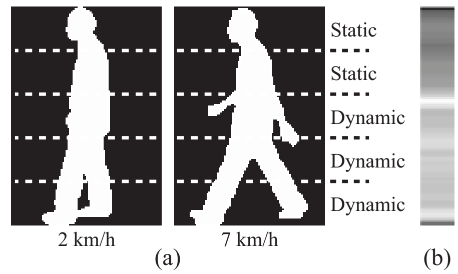


Fig. 1. (a) Examples of gait images in OU-ISIR Treadmill Dataset A [13]. These images show that there are dynamic areas and static ones while walking, (b) an example frieze pattern ($FP_h$) of 7 km/h.

In [9] we proposed a new idea that speed information does not have to be regarded as a critical information in gait recognition but appearance information is important, since speed can change easily due to external factors, such as crowded area and red traffic lights. Thus we regarded that an image set-based matching approach could solve the gait recognition problem. To show the effectiveness of this idea, we proposed a method [9] which applied a mutual subspace method (MSM) [17] to gait images. Experimental evaluations with a challenging gait database (OU-ISIR Gait Speed Transition Dataset [15]) showed that the MSM-based method [9] outperformed the state-of-the-art method [15].

We also evaluated the MSM-based method on another dataset (OU-ISIR Treadmill Dataset A [13], which was collected on a treadmill with speed variations), and those results are shown in experiments in this paper. In case that speed variations are small between gallery and probe dataset, the MSM-based method showed good performance. However, in case that the speed variations are big, such as fast walk (7 [km/h]) for gallery dataset and slow walk (2 [km/h]) for probe dataset (Fig. 1 (a)), the performance was worse than the RSM-based method [4]. We believe this could be because of the following reason. As we can see in Fig. 1 (a), there are dynamic areas and static areas while walking. Even though there is speed difference between images, static areas show similar appearance. On the other hand, dynamic

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areas show different appearance. The MSM-based method [9] used entire area in each image as input into MSM, and this causes decrease in performance because of the use of dynamic area.

In general in MSM, a set of images for each class are given as an input dataset into MSM and a model for each class is obtained as a subspace. To obtain the model, images are transformed into 1D image vectors, which are high dimensional vectors, and then principal component analysis (PCA) is used to generate subspace from input vectors. However, as Yang et al. [18] pointed out that the covariance matrix cannot be evaluated accurately due to its large size. Moreover, transforming 2D images into 1D image vectors results in reducing information of shape properties, due to the loss of geometrical information.

To deal with these issues, we propose a method, which expands the previous MSM-based method [9], to recognize people more robust to speed variations than the previous method. In the proposed method, the human body area in each image is divided into multiple areas, and MSM [9] is applied to each area. The idea of dividing area into small multiple areas, which we proposed in [10], is integrated in the MSM for the first time to the best of our knowledge. A matching weight at each area is calculated automatically, and areas which have higher discrimination capabilities are adaptively selected based on the calculated weights. Then the subject is identified by weighted integration of similarities of all areas.

Basically the use of divided areas has an advantage that it reduces the dimension of input vectors of MSM. This results in higher accuracy of the evaluation of the covariance matrix than the use of full area. The same advantage can be obtained by extracting gait features from images, which represent gait images efficiently with smaller size of feature vectors, rather than the direct use of image vectors as input into MSM. There are existing methods to extract features from gait images [14] [20] [12] [7], and among them we focus on frieze pattern [12] and affine moment invariants (AMIs) [7], which show high performance with small size of feature vector. In the proposed method we also utilizes gait features as input into MSM, in addition to image vectors. Moreover, these two gait features describe shape properties. Thus the use of gait features gives another advantage that it incorporates shape properties into the covariance matrix.

Overall, the proposed method has three advantages: (i) the extension of the MSM-based method by dividing the subject area into multiple areas [10] for the purpose of high accuracy of the evaluation of the covariance matrix, (ii) the extension of the MSM-based method using gait features (AMIs and frieze patterns), and (iii) the evaluation of the MSM-based method with two challenging gait databases, which consist of gait images with variety of speeds, such as OU-ISIR Treadmill Dataset A [13] and CASIA-C Dataset [1]. We experimentally confirm that the proposed method performs better than existing methods.

## II. Mutual Subspace Method Using Divided Areas for Gait Recognition

In this section we briefly review MSM. Then, we introduce a method to recognize people more robust to speed variations than existing methods.

### A. Mutual subspace method

MSM is regarded as one of powerful image set - image set matching techniques. Let us assume $C$ class pattern recognition problem. Bases of the class $c$ gallery subspace and input subspace are represented as $\boldsymbol{\phi}^c$ and $\boldsymbol{\psi}$, respectively.

Similarities in MSM are based on canonical angle $\theta_n^c$ ($n = 1, \ldots, N$, and $N$ is the number of canonical angles) between two subspaces. More specifically, a similarity $s_n^c$ is a square of a cosine of a canonical angle ($i.e.\ cos^2\theta_n^c$), and similarities are calculated as eigenvalues of the following matrix [2].

$$\boldsymbol{Z}^c = (\zeta_{ij})^c = \sum_{m=1}^{M} (\boldsymbol{\phi}_i^c \cdot \boldsymbol{\psi}_m)(\boldsymbol{\phi}_j^c \cdot \boldsymbol{\psi}_m). \tag{1}$$

In our method we use the maximum eigenvalue $s_1^c$ as the similarity between two subspaces. Class $c$ is chosen, in case that the maximum eigenvalue $s_1^c$ is the highest one among all classes.

### B. Proposed gait recognition method robust to speed variations

We explain the proposed method using divided areas, and we introduce the use of gait features as input into MSM.

*1) Mutual subspace method using divided areas:* The main steps of the gait recognition with MSM using divided areas are as follows:

- **Step 1** We divided each image in the gallery dataset and the probe dataset into $K$ equal areas, according to the height. Figure 1 (a) shows an example of a human body area divided into $K$ =5 areas.
- **Step 2** We applied MSM to images at each area, and at each area we calculated a similarity between each person in the gallery dataset and a subject in the probe dataset.
- **Step 3** We estimated a matching weight at each area according to the similarity. We set matching weights high in areas with less appearance changes and low in areas with appearance changes.
- **Step 4** Finally we identify the subject by weighted integration of similarities of all areas.

Details of Steps 2 to 4 are explained below.

In each of $K$ divided areas a similarity $s_{1,k}^c$ ($k$=$1, \ldots, K$) between gait images of the subject and those of class $c$ in the gallery dataset is calculated. Here, $s_{1,k}^c$ is calculated as the maximum eigenvalue from Eq. 1. Matching weights are estimated as follows. In each area similarities between the subject and all classes in the gallery dataset are sorted in a descending order, and a matching weight $w_k^c$ of each class is given according to its resulting order. Similarities of all areas are integrated by

$$S^c = \sum_{k=1}^{K} w_k^c s_{1,k}^c. \tag{2}$$

There are several ways to give the matching weights, and in the proposed method we set 1.0 to the class which has the highest similarity and 0.0 to the rest of classes. The subject is identified as a person $c$ in case that the final similarity $S^c$ is the highest one among all classes.

The above process allows us not to utilize similarities extracted from areas with low matching weights, which are due to speed change, but it allows to utilize similarities from areas with high matching weights. Therefore, the proposed method enables person identification robust to speed variations. Moreover, dividing the subject area into multiple areas makes a dimensionality of an input image vector into MSM smaller compared with that of the original image vector, and this allows the evaluation of the covariance matrix with higher accuracy.

*2) The use of image vectors and gait features:* As we explained in Section 1, there is an alternative way to make the dimensionality of input vectors into MSM small, that is the use of gait features extracted from images. There are several techniques to extract gait feature from each image. In this paper we focus on frieze pattern [12] and AMIs [7], since these two techniques reported good performance. We explain two methods briefly as follows.

Lee et al. proposed the frieze pattern [12], which has two feature vectors defined as $FP_h(y,t) = \sum_x I(x,y,t)$, and $FP_v(x,t) = \sum_y I(x,y,t)$. In this paper we used $FP_h(y,t)$ only, since the use of $FP_v(x,t)$ caused a decrease in performance. Figure 1 (b) shows an example image of feature vectors of frieze pattern.

Affine moment invariants [3] are moment-based descriptors, which are invariant under a general affine transform. The moments describe shape properties of an object as it appears. There are totally 80 independent AMIs, which are based on centralized moments $\mu_{pq}$ of order $(p+q)$, and one of 80 AMIs is defined as $I_1 = \frac{1}{\mu_{00}^4}(\mu_{20}\mu_{02} - \mu_{11}^2)$.

The process of gait recognition using gait features is basically the same with the one with image vectors as follows. After images are divided into $K$ areas, we extract $K$ feature vectors from each of gait images. Extracted feature vectors from gait images at each area are used as input into MSM, followed by calculation of matching weights in all areas. Matching weights are calculated in the same way with the ones in Section II-B.1. Finally the subject is identified by weighted integration of similarities of all areas.

We did preliminary experiments on OU-ISIR Treadmill Dataset A [13] to compare the performance between the frieze pattern and AMIs. We did matching between gait images of 2 km/h (gallery) and those of 2 $\sim$ 7 km/h (every 1 km/h, probe). Table I shows correct classification ratios of frieze pattern and AMIs, each of which is applied to the proposed method. Parameters in the proposed method, which are the number of divided areas $K$ and dimensionalities of subspaces of gallery and probe dataset, are selected with datasets for parameter training as we explain in experiments. These results show the frieze pattern is better than AMIs. This could be because of the following reason. From the definition of frieze pattern, we can say that each element of frieze pattern is correlated, since we can assume that the human body shape is smooth. On the other hand, each element of AMIs is independent. Intuitively, in case that correlations among feature elements are strong, feature vectors in each class can be represented with a lower dimension subspace. This results in reducing the possibility that subspaces among classes overlap each other, and this may allow higher performance. Thus in the experiments, we use the frieze pattern.

TABLE I

COMPARISON OF CORRECT CLASSIFICATION RATIO (CCR) [%] OF FRIEZE PATTERN [12] AND AMIS [7], EACH OF WHICH IS USED AS INPUT INTO MSM. THE SPEED OF GALLERY DATASET IS 2 KM/H, AND THOSE OF PROBE DATASET IS EACH OF 2 $\sim$ 7 KM/H.

| | Probe [km/h] | | | | | |
|---|---|---|---|---|---|---|
| | 2 | 3 | 4 | 5 | 6 | 7 |
| Frieze pattern [12] | 100 | 100 | 100 | 100 | 100 | 92 |
| AMIs [7] | 100 | 100 | 100 | 96 | 84 | 80 |

Since the frieze pattern represents shape properties, the use of frieze pattern allows to incorporate shape properties into the covariance matrix. On the other hand, as we explained in Section 1, the use of image vectors does not incorporate shape properties into the covariance matrix. We can expect the use of both image vectors and gait features may lead to higher performance than the use of each of them, since these two have different properties. Thus in our method we use both as input into MSM.

## III. EXPERIMENTS

In this section, we implement the proposed method and evaluate its performance on OU-ISIR Treadmill Dataset A [13] and CASIA-C Dataset [1]. The OU-ISIR Treadmill Dataset A was collected on a treadmill with speed variations (from 2 km/h to 10 km/h, every 1 km/h). The CASIA-C Dataset was collected at night using infrared cameras with several conditions including standard, speed, and carrying variations.

### A. Gait recognition with the OU-ISIR Treadmill Dataset A

The OU-ISIR Treadmill Dataset A consists of gait images for 34 people, and from the dataset specification, 25 subjects and the rest of subjects are assigned for evaluation and parameter training, respectively. In our method we have parameters, *i.e.*, the dimensionalities of subspaces of gallery and probe dataset, and the number of divided areas $K$, and these parameters are tuned with datasets for parameter training.

This dataset consists of gait images with speed variations (from 2 km/h to 10 km/h, every 1 km/h)) for each gallery and probe dataset, and subjects walked for speeds between 2 km/h to 7 km/h and run for speeds between 8 km/h to 10 km/h. In this section we used images for speeds between 2 km/h to 7 km/h, and we did experimental evaluations with all combinations of gallery and probe speeds, *i.e.* 36

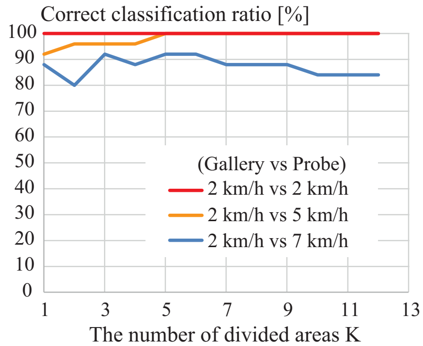



Fig. 2. Correct classification ratio with respect to changes of the number of divided areas $K$. We did matching between 2 km/h (gallery) and each of 2, 5, and 7 km/h (probe).

combinations ("6 different speed for each gallery dataset" $\times$ "6 different speed for each probe dataset").

In the first experiments, we changed the parameter $K$ to see the performance changes with respect to the change of $K$. We did matching between 2 km/h (gallery) and each of 2, 5, and 7 km/h (probe). We used image vectors as input into MSM, and parameters of gallery and input subspaces are tuned at each $K$. Figure 2 shows correct classification ratio (CCR) with $K$=1$\sim$ 12. Here, the result of $K$=1 is equal to the result of the MSM-based method [9]. From these results, we can see that the proposed method which uses divided areas is better than the MSM-based method [9], in case that we choose proper parameters.

Table II show results of cross-speed walking people identification by the proposed method with image vectors, the proposed method with frieze pattern, and the proposed method with image vectors and frieze pattern. The use of both image vectors and frieze pattern show the best performance compared with the one of either image vector or frieze pattern. Here, parameters of gallery and input subspaces and the number of divided areas $K$ are tuned simultaneously. Please note that some of results in Table II are different from those in Table I, since the way how parameters are tuned is different.

Moreover, we compared results with the RSM-based method [4], which showed the best performance with the dataset, and results of [4] are shown in Table III. Our method shows better performance than those of [4]. Table IV lists the average classification ratios of the MSM-based method [9] (96.78 %), our proposed method (image vector, 97.89 %), our proposed method (frieze pattern, 98.78 %), our proposed method (image vector and frieze pattern, 99.78 %), and the RSM-based method [4] (98.07 %). These results show the effectiveness of the proposed method with image vector and frieze pattern.

### B. Evaluation of effectiveness of the matching weights

To evaluate the effectiveness of the matching weights $w_k^c$ in Eq. 2, which are set as 1.0 to the class with highest similarity and as 0.0 to the rest of classes, we first checked the performance at each area of $K$ divided areas. Here, we used $K$=1$\sim$3 as examples. Correct classification ratio for each area between 2 km/h (gallery) and each of 2 $\sim$ 7 km/h (probe) is shown in Table V. These results supports the idea, which we mentioned in Section 1, that static areas have higher discrimination capabilities than dynamic areas. Interestingly, even though speeds of probe and gallery datasets are the same (i.e. 2 km/h for both probe and gallery), the area "3-3" has lower discrimination capability (28 [%]).

We checked a weight assigned to each area and Fig. 3 shows examples of assigned weights between gallery ID "28" and probe ID "28" ($K$= 2 and 3). From these results, we can see that higher weight (1.0) and lower weight (0.0) are set to static and dynamic areas, respectively. We confirmed that the proposed method successfully assigns high weights to areas which have higher discrimination capabilities.

We also did cross speed walking gait recognition with $w_k^c$=1.0 for all classes (*i.e.* simple summation of similarities of all areas). Figure 4 shows results of matching between 2 km/h (gallery) and each of 2 $\sim$ 7 km/h (probe) by (a) proposed matching weights and (b) equal matching weights. Here, we used image vectors and frieze pattern as input into MSM. These results show that the use of proposed matching weights improve the performance of gait recognition.

### C. Gait recognition with the CASIA-C Dataset

In the last experiments we evaluated the proposed method (image vectors and frieze pattern) on the CASIA-C Dataset, which consists of 153 subjects with 3 different walking speeds and a carrying condition. Since this paper focuses on walking speed condition, we apply the proposed method to datasets of different walking speeds. Three walking conditions contain normal walking ($fn$), slow walking ($fs$), and fast walking ($fq$). For each subject, there are 4 sequences of $fn$, 2 sequences of $fs$, and 2 sequences of $fq$. We used 3 normal walking ($fn$) sequences as the gallery set, and the rest sequences were used as the probe set.

Table VI shows the results of the proposed method, the RSM-based method [4], the DLT-based method [19], and AEI [20] for each of $fn$, $fs$, and $fq$. These results show the effectiveness of the proposed method.

## IV. Conclusions

This paper described a method, which expanded the previous MSM-based method [9], to recognize people more robust

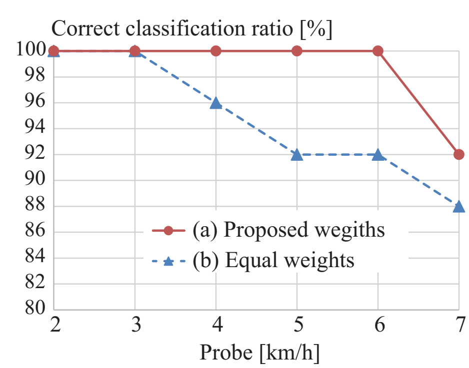



Fig. 4. Correct classification ratio between 2 km/h (gallery) and each of 2 $\sim$ 7 km/h (probe), with (a) proposed matching weights and (b) equal matching weights $w_k^c$=1.0.

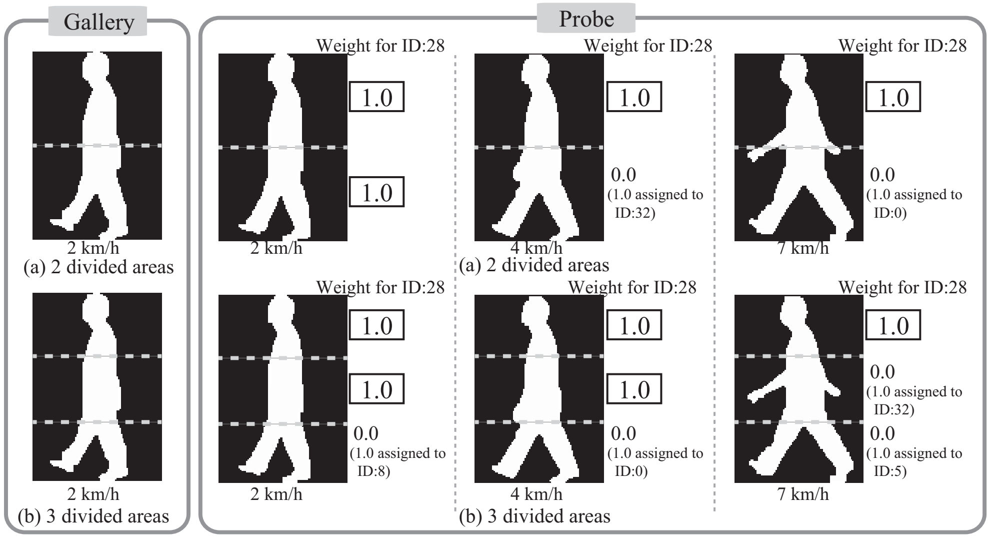



Fig. 3. Examples of weights assigned to areas of $K$(=2 and 3) divided areas. These results show weights between gallery ID "28" and probe ID "28", and numbers next to pictures show assigned weight.

TABLE II

CORRECT CLASSIFICATION RATIO OF THE PROPOSED METHOD WITH (I) IMAGE VECTOR, (II) FRIEZE PATTERN, AND (III) IMAGE VECTOR AND FRIEZE PATTERN IN THE CROSS-SPEED WALKING GAIT RECOGNITION. RESULTS ARE SHOWN AS (I, II, III).

| Gallery \ Probe | 2 km/h | 3 km/h | 4 km/h | 5 km/h | 6 km/h | 7 km/h |
|---|---|---|---|---|---|---|
| 2 km/h | (100, 100, 100) | (100, 100, 100) | (100, 100, 100) | (96, 100, 100) | (96, 100, 100) | (92, 88, 92) |
| 3 km/h | (100, 100, 100) | (100, 100, 100) | (96, 100, 100) | (100, 100, 100) | (100, 100, 100) | (92, 96, **100**) |
| 4 km/h | (100, 100, 100) | (100, 100, 100) | (100, 100, 100) | (96, 100, 100) | (96, 100, 100) | (96, 96, **100**) |
| 5 km/h | (100, 100, 100) | (100, 100, 100) | (100, 100, 100) | (100, 100, 100) | (100, 100, 100) | (96, 100, 100) |
| 6 km/h | (100, 100, 100) | (100, 100, 100) | (100, 100, 100) | (100, 100, 100) | (100, 100, 100) | (100, 100, 100) |
| 7 km/h | (88, 84, **100**) | (92, 92, **100**) | (88, 100, 100) | (96, 100, 100) | (100, 100, 100) | (100, 100, 100) |

TABLE III

CORRECT CLASSIFICATION RATIO OF THE RSM-BASED METHOD [4] IN THE CROSS-SPEED WALKING GAIT RECOGNITION.

| Gallery \ Probe | 2 km/h | 3 km/h | 4 km/h | 5 km/h | 6 km/h | 7 km/h |
|---|---|---|---|---|---|---|
| 2 km/h | $100\pm0.00$ | $100\pm0.00$ | $100\pm0.00$ | $97.6\pm2.07$ | $97.6\pm2.80$ | $\mathbf{94}\pm2.83$ |
| 3 km/h | $100\pm0.00$ | $100\pm0.00$ | $100\pm0.00$ | $100\pm0.00$ | $100\pm0.00$ | $98.4\pm2.07$ |
| 4 km/h | $100\pm0.00$ | $100\pm0.00$ | $100\pm0.00$ | $100\pm0.00$ | $100\pm0.00$ | $90.4\pm2.80$ |
| 5 km/h | $92.8\pm1.69$ | $96.4\pm1.26$ | $100\pm0.00$ | $100\pm0.00$ | $100\pm0.00$ | $96\pm0.00$ |
| 6 km/h | $92\pm0.00$ | $94.4\pm2.07$ | $100\pm0.00$ | $100\pm0.00$ | $100\pm0.00$ | $100\pm0.00$ |
| 7 km/h | $92\pm0.00$ | $94\pm2.11$ | $94.8\pm1.93$ | $100\pm0.00$ | $100\pm0.00$ | $100\pm0.00$ |

TABLE IV

COMPARISON OF AVERAGE CORRECT CLASSIFICATION RATIO (CCR) [%] OF EACH MSM-BASED GAIT RECOGNITION [9], OUR PROPOSED METHOD (IMAGE VECTOR), OUR PROPOSED METHOD (FRIEZE PATTERN), OUR PROPOSED METHOD (IMAGE VECTOR AND FRIEZE PATTERN), AND RSM-BASED GAIT RECOGNITION [4] ON OU-ISIR TREADMILL DATASET A [13].

| | MSM-based gait recognition [9] | Our proposed method (image vector) | Our proposed method (frieze pattern) | Our proposed method (image vector and frieze pattern) | RSM-based gait recognition [4] |
|---|---|---|---|---|---|
| CCR [%] | 96.78 | 97.89 | 98.78 | **99.78** | 98.07 |

to speed variations than the previous method. In the proposed method, the human body area in each image was divided into multiple areas, and MSM [9] was applied to each area. A matching weight at each area was calculated automatically, and areas which had higher discrimination capabilities were adaptively selected based on the calculated weights. Then the subject was identified by weighted integration of similarities of all areas. The proposed method has an advantage that it can adaptively choose areas that have high discrimination capability. Moreover, in the proposed method we utilized the frieze pattern as an input into MSM. The use of divided areas and the frieze pattern allowed us to evaluate the covariance matrix in MSM with higher accuracy, which resulted in higher performance in gait recognition. We carried out exper-

TABLE V

CORRECT CLASSIFICATION RATIO AT EACH AREA OF $K$ DIVIDED AREAS ($K$=1 $\sim$ 3). THE SPEED OF GALLERY DATASET IS 2 KM/H, AND THOSE OF PROBE DATASET ARE 2 $\sim$ 7 KM/H. THESE RESULTS SHOW THAT STATIC AREAS HAVE HIGHER DISCRIMINATION CAPABILITIES THAN DYNAMIC AREAS. BOLD NUMBERS SHOW RELATIVELY HIGH PERFORMANCE.

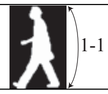
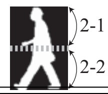
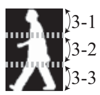
| The number of divided areas ($K$) | Area | 2 km/h | 3 km/h | 4 km/h | 5 km/h | 6 km/h | 7 km/h |
|---|---|---|---|---|---|---|---|
| 1  | 1-1 | 100 | 96 | 96 | 72 | 72 | 60 |
| 2  | 2-1 | 100 | 88 | 100 | 96 | 88 | 84 |
| | 2-2 | 72 | 72 | 40 | 28 | 4 | 8 |
| 3  | 3-1 | 96 | 92 | 88 | 88 | 76 | 84 |
| | 3-2 | 60 | 68 | 44 | 16 | 20 | 12 |
| | 3-3 | 28 | 24 | 4 | 12 | 4 | 4 |

TABLE VI

COMPARISON OF AVERAGE CORRECT CLASSIFICATION RATIO (CCR) [%] OF EACH OF THE PROPOSED METHOD (IMAGE VECTOR AND FRIEZE PATTERN), RSM-BASED GAIT RECOGNITION [4], DLT-BASED GAIT RECOGNITION [19], AND AEI [20] ON CASIA-C [1]

| | Our proposed method (image vector and frieze pattern) | RSM-based gait recognition [4] | DLT-based gait recognition [19] | AEI [20] |
|---|---|---|---|---|
| $fn$ | 100 | 100 | 95.4 | 89 |
| $fs$ | 99.7 | 99.7±0.24 | 91.2 | 89 |
| $fq$ | **99.7** | 99.6±0.14 | 92.5 | 90 |

iments with two gait databases, and showed the robustness of the proposed method compared with conventional methods against speed changes.

In this paper the proposed method was evaluated with datasets of speed changes, but theoretically the method can work with datasets of different variations such as clothes changes. This is left as a future study.

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